A Virtual Reality and Brain Computer Interface System for Upper Limb Rehabilitation of Post Stroke Patients

David Achanccaray, Kevin Acuña, Erick Carranza
Department of Engineering
Pontifical Catholic University of Peru
Lima, Peru
dachanccaray@pucp.pe, kjacuna@pucp.pe,
erick.carranza@pucp.pe

Javier Andreu-Perez
Department of Computing, The Hamlyn Centre,
Institute of Global Health and Innovation
Imperial College London
London, UK
javier.andreu@imperial.ac.uk

***Abstract*—This work presents a brain computer interface (BCI) framework for upper limb rehabilitation of post stroke patients, combining BCI and virtual reality (VR) technology; a VR feedback is shown to the participants to achieve a greater activation of certain brain regions involved with the performing of upper limb motor task. This system uses an adaptive neuro-fuzzy inference system (ANFIS) classifier to discriminate between a motor task and rest condition, the first one classifies between extension and rest conditions; and the second one classifies between flexion and rest conditions. In the training stage, eight healthy subjects participated in the sessions, the best accuracies are 99.3% and 88.9%, as a result of cross-validation. Meanwhile, the best accuracy in online test is 89%. The methodology here presented can be straightforwardly employed as a rehabilitation system for brain repair in individuals with neurological diseases or brain injury.**

***Index Terms*—Brain Computer Interface, Rehabilitation, Virtual reality, ANFIS**

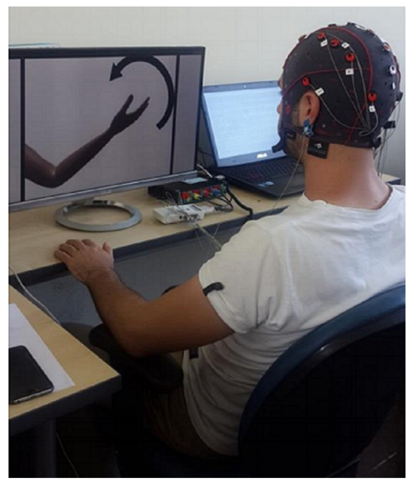

Fig. 1. Participant in the study.

I. Introduction

Stroke is a multifactor and chronic disease, there are approximately 15 million people suffering of stroke per year, and 6 million dying [1]; a consequence of stroke is the partial or total palsy of the patient extremities, a physical therapy of rehabilitation is needed for motor recovery. Many times, rehabilitation therapies take long times due to the loss of patient's interest, and deficit in human and technological resources [2]. For this reason, brain computer interfaces (BCI) are proposed as assistive technology for rehabilitation to reduce recovery times.

BCI's have been used in many applications, due to the advancement of the technology in the last decades; application main areas are communication and control, motor rehabilitation, motor substitution, mental state monitoring, and entertainment [3]. A BCI for motor rehabilitation stimulates the neuroplasticity phenomena in post stroke patients, it must identify the neural damage intensity of the patient to design a suitable BCI protocol; it can vary depending on the chosen limb for motor recovery.

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First studies applying a BCI on stroke patients found suited features in signals from unaffected hemisphere [4]; mental task based on BCI protocols contribute with the positive effects of classical therapies, signal processing in [5] identifies brain activity patterns while performing the task. Furthermore, BCI is approached like a training tool to recover hand motor functions in patients suffered stroke [3]; a study involving a large number of patients developing BCI training based on kinesthetic motor imagery (MI) combined with robotic therapy reported improvements in motor function compared to baseline, although there were not important differences compared to neurobotic training alone [6]. Other two cases reported improvements in rehabilitation after BCI training alone [7] [8].

Currently, two types of BCI applications for stroke rehabilitation are being investigated. Both strategies are focusing on neuroplasticity and its modulation [3]. The first approach

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consists to use BCI for patient's training to reconstitute regular brain responses associated to motor activity, it is based on the hypothesis of more brain responses produced by regular brain function probably improve motor control; evidence in human and animals involved in conditioning experiments showed changes in brain activity [3]. The second one is to operate devices through BCI's, these devices are designed to assist movements, evidence in subjects observing or practicing movements normally performed in healthy conditions could contribute to improve motor function, these assisted movements generate sensory inputs to the suitable brain regions [3]. In a study develop by Buch [4], eight stroke patients without finger function in their affected hand participated in a BCI based on magnetoencephalography (MEG) experiments, they were asked to modulate their sensorimotor rhythms (SMR) during MI tasks of their affected hand to control a mechanical orthosis that flexes or extends their fingers. Features that discriminate MI tasks from the rest condition were selected from the MEG analysis independently of their location in the brain [3].

In MI-based BCI, feedback accomplishes a significant role in the patient's training; it can be done through observations of signals in a screen, movements of mechanisms or robots, or 3D graphs in virtual reality (VR). VR in BCI applications provides to the subject an immersive environment and feedback to interact in real time [3]. A subject with total palsy employs a MI-based BCI to move a wheelchair in VR [9], this was the first time that a tetraplegic patient could control a virtual device. 5 chronic hemiplegic stroke patients perform sessions of physical practice and MI practice of a therapeutic task, the performed or imagined hand clenching; positive improvements were observed in all participants, they presented moderate range of accuracy 60-75% for the BCI classifier in the training stage, but it did not impede the positive rehabilitation trends [10]. Mirror therapy (MT) is the reflection of the movement of the unaffected limb superimposed on the paralyzed limb, applying VR to simulate MT increases the brain activity in the sensorimotor cortex in response to the simulated movement [11].

Machine learning algorithms that can simultaneously adapt and model uncertainty on brain signal observations are a key component for reliable and real-time BCI control [12]; type-2 fuzzy sets are associated to ANFIS classifier for a BCI application where a multiclass classification is carried out by the combination of binary classifiers using type-2 fuzzy sets to calculate the output [13]; it was applied in a MI-based BCI to control an arm robot using five mental tasks, eleven subjects participated in this experiment, the best accuracy is 99.5% in training stage and 80% in online test. In [14], ANFIS time series predictor and multiresolution fractal vectors were applied to extract features in MI classification. It was compared with other prediction techniques, but ANFIS got the best accuracy equal to 91.4% in training stage and 86.3% in online test.

This work proposes a MI-based BCI and VR feedback as an assistive technology to increase the activation on brain region to contribute with the upper limb rehabilitation treatment of post stroke patients, the brain activity is recorded by an electroencephalograph (EEG). An adaptive neuro-fuzzy algorithm, ANFIS, is used to evaluate the performance of a VR-BCI system.

This paper is organized as follows: Section II presents the data description and experimental procedure developed. In section III, the data processing techniques used for offline classification and online control or the virtual arm are discussed. The results of the offline and online tests are presented in Section IV, followed by the conclusions given in Section V.

II. Experimental procedure

A. Participants

Eight healthy male subjects were recruited for the study. Participants were recruited at the university, the men average age was 25, and all participants had received bachelor degree. Every subject read and signed an ethical consent and was informed about the test. Participants also agreed to use their images and videos for dissemination purposes.

B. Data Acquisition

EEG data was recorded using a 16-channel g.USBAmp amplifier and 16 g.LADYBird active electrodes (from g.tec medical engineering GMBH, Austria). The 16 electrodes were uniformly distributed around the motor cortex over the scalp (Fig 2), following the 10/10 international system with the ground at Fz and referenced to the left ear lobe. Data was bandpass filtered from 0.1 to 30 Hz and a 60 Hz notch filter was applied. Sampling frequency used was fs = 256 Hz.

C. Virtual Arm

To provide visual feedback to the user, a virtual human arm (avatar) was developed (Fig 4). The avatar was built using 3 software: Makehuman, to obtain the shape and characteristics of an arm; Blender, to make the animations; and Unity, to obtain the final interactive application and communication. The virtual arm performs the 3 positions required: flexion,

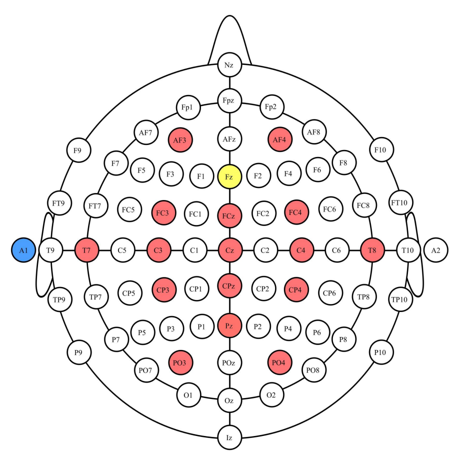

Fig. 2. EEG Electrodes positions.

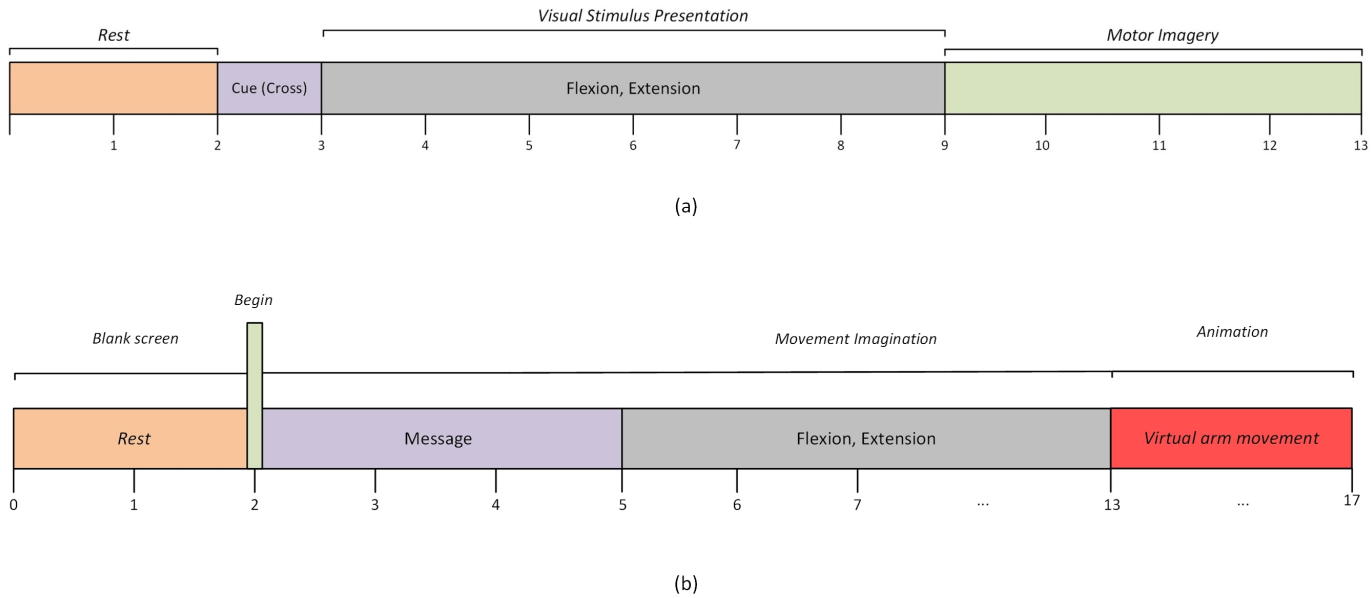

Fig. 3. Timelines. (a) Training Stage. (b) Online Test.

extension and rest. The virtual arm was controlled through a User Diagram Protocol (UDP) connection between Simulink and Unity.

D. Training Stage

Participants were seated in a chair, in front of a computer screen, with both forearms resting in their lap (Fig 1). Subjects were asked to stay relaxed and still during the course of the experiment. Participants were also asked to limit eye movements. Fig 3 (a) shows the paradigm of data acquisition with visual stimuli. A black screen was shown the first 2 seconds, during this time, the participant was in the 'relax' state. Immediately after, a visual cue (cross) was displayed for 1 second, indicating the motor imagery task was about to start. From t=3 to t=9, an image was presented. This image presented an arm with an arrow pointing "inside" or "outside", which meant flexion or extension movement imagination respectively. Each run consisted on 20 trials (10trials/class) and a total of 5 runs were recorded, 100 trials in total. After each run, a 30s break was performed.

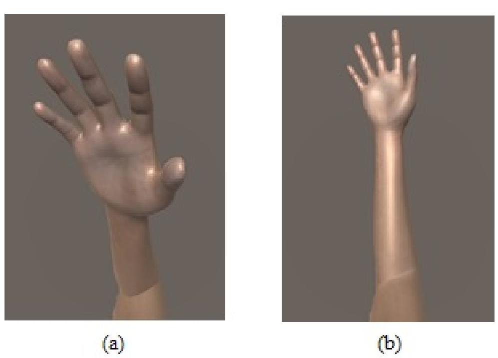

Fig. 4. Virtual arm. (a) Flexion. (b) Extension.

E. Online Test

A real time test was required to evaluate the algorithm efficiency and accuracy (Fig 3 (b)). First, the participant was comfortably seated on a chair, in front of a screen. The screen provided the visual feedback to the user. At t=0, a blank screen was presented for two seconds, at this moment, the user was calmed and relaxed. At t=2s, a message appeared showing the movement the participant needed to imagine, either flexion or extension. This message was shown for 3s and then disappeared. From t=5s to t=13s, the user had to imagine the movement presented by the message. During this period of time, the algorithm computed the EEG data recorded. At t=13s, the avatar performed the movement thought, depending on the output of the classifier. If the classification was successful, the avatar performed the required movement, if not, the avatar did not move and remained in the same position. The avatar animation had a duration of 4 seconds. Finally, the trial started again.

III. Processing

A. Re-reference

A Reference electrode was positioned on the left ear lobe, meaning that the EEG signal measured, is the difference between each electrode and the reference electrode. However, this is not always the most accurate method to measure EEG, therefore, the reference is modified. This process is known as re-reference and aims at increasing signal quality. Common Average Reference (CAR) was applied to the data. This spatial filter is used to re-reference the electrodes in relation to the

average value, improving the signal quality for each channel. The mathematical formula that explains CAR is shown in Eq.1.

$$\tilde{eeg_i} = eeg_i - \frac{1}{N}\sum_{i=1}^{N} eeg_i \quad (1)$$

where i is the number of channel, and eeg is the EEG signal.

B. Butterworth Filter

For optimal feature extraction between motor imagery bands, EEG signal analysis in frequency domain is necessary. Major amplitude and energy changes are found on mu (8-13Hz) and beta (13-30Hz) frequency bands, on the premotor and primary sensorimotor areas of the brain. The frequencies outside this range were attenuated using a third order bandpass Butterworth filter.

C. Feature Extraction

Feature extraction is performed by applying common spatial patterns and re-scaling theses features through a log-transformation.

1) Common Spatial Patterns: The common spatial pattern (CSP) algorithm is widely applied in BCI. This method relies on obtaining the Z matrix by decomposing the EEG data. This matrix leads to optimal discrimination of two sets of observations of EEG data by returning the highest variance and lowest variance in its first and last columns respectively, each representing a different class. For this study, the first and last 3 columns of Z matrix were selected. This way, the initial 16 columns of EEG data were decomposed into 6 column matrix.

2) Log-Transformation: A logarithmic transformation (Eq.2) is applied to the variance of the Z reduced matrix, to approximate a normal distribution of the data. This leads to a feature vector composed by the 6 previous values, which is used to train the classifier.

$$f = \log\left(\frac{var(Z_p)}{\sum var(Z_p)}\right) \quad (2)$$

where Z_p is the reduced matrix.

D. Classification

In ANFIS, the parameters of the fuzzy inference system are tuned by an adaptive neuro-fuzzy network. Due to its adaptive feature, ANFIS can cope with the time-variant behavior of the EEG signals. ANFIS is composed by 5 layers. Layer 1 computes the membership degree of an EEG observation. Layer 2 is a T-norm operator (AND) that outputs the firing strength of a rule. Layer 3 normalizes the firing strengths. Layer 4 yields the output values resulting from the inference. This is computed by a product of the outputs from layer 3 and a first order polynomial; the coefficients of this linear combination are called consequent parameters. Layer 5 performs aggregation by adding up all outputs of the previous layer [13].

ANFIS classifier was chosen to discriminate between classes. The ANFIS classifier was integrated into the VR-BCI using the Adaptive Neuro-Fuzzy Inference Systems (ANFIS) Library for Simulink, which is available on Mathworks File Exchange [15]. Table I shows the parameters used on the ANFIS classifier.

TABLE I
ANFIS PARAMETERS.

Membership function	Input number	Output number	Parameters	
			Learning Rate	Momentum
Generalized Gaussian function	6	1	0,001	0,0025

In this system, the rehabilitation therapy consists on performing flexion and extension movement imagination in different moments; thereby, two classifiers were trained. The first classifier discriminated between rest and extension movement imagination, while the second classifier discriminated between rest and flexion conditions.

IV. RESULTS

A. Training Stage

EEG data was recorded for each subject as described in part E of the experimental procedure. For each class, data was divided in 1 second windows and overlapped into 900 milliseconds windows, to increase the number of trials to train the classifier. CSP matrix was obtained for each binary case (flexion-rest, extension-rest). Logarithmic transformation was applied to these matrices to retrieve standardized data to train the ANFIS classifiers. Data was randomized and partitioned for training (80%) and testing (20%). ANFIS classifier was trained and validated using 5-fold cross-validation. Results are shown in Table II.

Fig 5, shows that the EEG activity between classes was differentiated for each motor imagery task, brain activity in the selected channels evidence the motor activation.

Table II shows the accuracy (Acc), True Positive Rate (TPR) and True Negative Rate (TNR) per subject, the first and the third subjects show greater accuracies for both classifiers. The mean value obtained by the other subjects also shows a meaningful value.

B. Online Test

Four of eight participants took part of the online test. Each trial, consisted on developing a certain sequence of 20 motor

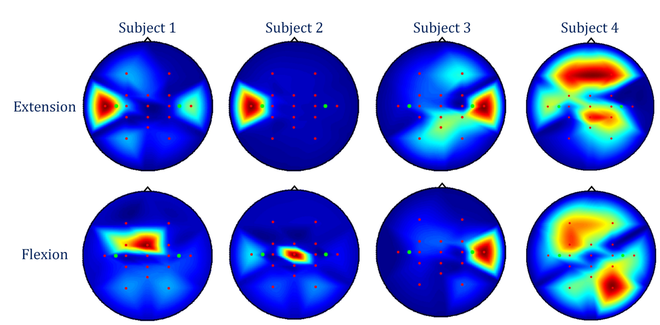

Fig. 5. CSP Result.

TABLE II
CROSSVALIDATION OF TRAINING STAGE ACCURACIES FOR THE REST-FLEXION CLASSIFIER AND THE REST-EXTENSION CLASSIFIER.

Subject	Rest-Extension			Rest-Flexion		
	Acc(%)	TPR	TNR	Acc(%)	TPR	TNR
S1	99,3	0,98	0,99	88.9	0,89	0,79
S2	77,5	0,81	0,72	81.1	0,83	0,74
S3	89,8	0,96	0,82	70.2	0,83	0,66
S4	80,4	0,81	0,80	71,2	0,80	0,64
S5	77,2	0,79	0,71	76,4	0,78	0,47
S6	78,6	0,81	0,64	76,1	0,78	0,42
S7	78,1	0,80	0,54	78,1	0,78	0,52
S8	72,6	0,74	0,25	79,8	0,81	0,66
Mean	81,7	0,83	0,68	77,7	0,81	0,61

TABLE III
ACCURACY OF ONLINE TESTS.

Subject	Accuracy (%)	F-score
S1	81	0,82
S2	69	0,79
S3	89	0,87
S4	67	0,78
Mean	76,5	0,81

tasks divided into flexion, extension and rest. Every subject performed a total of four trials for each task. As shown in Table III, all of the participants achieved a considerably good accuracy during the online test; however, in online test the first and third subjects also have greater accuracies.

V. CONCLUSIONS

A VR-BCI framework for upper limb rehabilitation is proposed, combining BCI and VR technology to increase the activation in certain brain regions involved in performing movement related to the upper limb. This system was tested with healthy subjects, resulting in accuracies greater than 77% and the best case being 99.3% in the training stage, and 89% in online tests. These results demonstrate the possibility to apply this system to stroke patients with upper limb motor disease or dysfunction such as post stroke patients.

The study demonstrates that the adaptive and fuzzy capabilities provided by an algorithm like ANFIS are suitable to discriminate between motor imagery and rest in a VR-BCI environment. In future research, spatial ability test and anxiety test will be taken to all participants to evaluate their predisposition to different types of VR-BCI applications. Additionally, we will extend the present work to other more sophisticated neuro-fuzzy algorithms as well as different motor imagery tasks using immersive VR.

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